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The Effects of Digital-Technology Adoption on Productivity and Factor Demand

Firm-level Evidence from Developing Countries

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Abstract

This paper presents firm-level estimates of revenue-based total factor productivity premiums of manufacturing firms adopting digital technology in 82 developing economies over 2002–19. The paper estimates productivity using the control function approach and assuming an endogenous revenue-based total factor productivity process, which is a function of multiple firm-choice variables. It estimates the effects of digital technology adoption, learning by exporting, and managerial experience on revenue-based total factor productivity and factor demand. The results reject the null hypothesis of an exogenous revenue-based total factor productivity process, in favor of one in which digital technology adoption, along with the other choice variables, affects revenue-based total factor productivity and factor demand. The estimated premiums are positive for 67.3 (email adoption), 54.6 (website adoption), 59.4 (learning by exporting), and 60.6 (managerial experience) percent of the sample. The probability-adjusted median (log) revenue-based total factor productivity premium associated with email adoption is 1.6 percent and that of website adoption is 2.2 percent, with the latter being higher than the premiums corresponding to exporting and managerial experience. On average, changes in digital technology adoption, email, and website are labor and capital augmenting. The paper also explores the role of complementarities among the firm choice variables.

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The Effects of Digital-Technology Adoption on Productivity and Factor Demand: Firm-level Evidence from Developing Countries*

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1 Introduction

The global digital economy accounted for 15.5 percent of the world's GDP in 2016 ($11.5 trillion). Yet, not everybody has benefited equally from the arrival of digital technologies. There are still huge disparities across and within countries when it comes to the adoption and usage of digital technologies (Comin and Mestieri 2018). While more than half of the world's population now has access to the internet, the penetration rate in the least developed countries is only 15 percent, or 1 in 7 individuals (World Development Report 2019).[1]

The benefits of adopting digital business solutions like email, launching a business website, or connecting to two-sided digital platforms can be substantial especially for firms (Goldfarb and Tucker 2019). The transfer of information and data over the internet helps reduce production costs and expand demand for a firm's goods and services and thus for its factors of production. Reductions in search costs enable buyers and sellers of products or services to get better access to the other side of the market, by increasing the speed or efficacy with which firms find workers or input suppliers (De Loecker 2019). Digital business solutions also help expand market opportunities. Reductions in search, transaction, or tracking costs allow firms to overcome geographical barriers, penetrate new markets, and enlarge the volume of trade (World Development Report 2020).

The existing evidence on the impact of digital-technology adoption on productivity and factor demand, however, is surprisingly thin, especially for developing countries. It is even thinner when it comes to quantifying these effects using firm-level data. This paper aims to fill these gaps in the literature. Specifically, we estimate the effects of adopting digital business solutions, namely email to communicate with clients and suppliers and launching a business website, on firm-level revenue-based total factor productivity (TFPR) and demand for labor and capital. We rely on publicly available data from the World Bank's Enterprise Survey database (WBES), which collects information on sales, factor and input usage, exporting status, managerial experience, and digital-technology adoption at the manufacturing

1. https://www.worldbank.org/en/topic/digitaldevelopment/overview.

firm level from a sample of 82 developing economies with data from 2002-2019.

To estimate TFPR, we first estimate a log-linearized Cobb-Douglas production function (PF) following Ackerberg, Caves, and Frazer (2015). Although, the Ackerberg, Caves, and Frazer (2015) method, which builds on Olley and Pakes (1996) and Levinsohn and Petrin (2003), assumes an exogenous productivity process, we follow De Loecker (2013) and endogenize TFPR. Thus, TFPR is a function of the adoption of digital business solutions (e.g., email and website) in addition to other firm-choice variables that can also affect firm performance, such as exporting and managerial experience, which have been studied separately in the literature. We validate our data and methodology by replicating the results presented in De Loecker (2013) for the specification that only includes learning-by-exporting effects. The evidence indicates that our estimates of the production function parameters and the coefficients of the endogenous productivity process, covering 82 developing countries, are highly correlated across industries with those reported by De Loecker (2013), for Slovenia.

Assuming an exogenous TFPR would have implied that digital technologies would have no impact on efficiency or sales. This is not only unrealistic but also, from a methodological point of view, would have invalidated the moment conditions needed to identify the coefficients of the production function. In other words, if TFPR is a function of business digitization that does, in fact, affect factor demand, the estimated production-function elasticities would be biased. The sign of the bias is ambiguous, depending on whether digitization is factor-augmenting or factor-saving. If business digitization is factor-augmenting, then TFPR would be underestimated. If improvements in TFPR are factor-saving, the effect of digitization on TFPR would be overestimated.

There are good reasons to expect that firm TFPR is a function of business digitization, as well as of exporting, as in De Loecker (2013), and managerial experience, as in Bloom and Van Reenen (2007) and Bloom and Van Reenen (2010). Using email to connect with clients or suppliers or having a business website to gain online presence can affect TFPR through different channels. On the demand-side, reductions in search and transaction costs affect firm profitability at the extensive and intensive margins, by facilitating access to new clients or expanding the volume of transactions online. Dynamically, the scale-up of the demand for a firm's products or services increases profits, allowing it to pay the fixed cost of investing in TFPR-enhancing activities like innovation, managerial upgrading, or technology adoption. On the supply-side, using email to connect with suppliers helps improve production efficiency, enlarging the potential set of input providers in non-relationship specific investments.

The results indicate that estimated TFPR-premiums are positive for 67.3 (email adoption), 54.6 (website adoption), 59.4 (learning by exporting), and 60.6 (managerial experience) percent of the estimation sample, respectively. The probability-adjusted median TFPR-premium associated with email adoption is 1.6 percent and that of website adoption is 2.2 percent. The probability-adjusted median TFPR-premium from getting access to external markets is 1.6 percent, while that of increasing the years of experience of the manager is near zero. Last, on average, changes in digital-technology adoption are labor- and capital-augmenting. TFPR improvements are also labor-augmenting, while they do not have any impact on the demand for capital. These findings are new to the existing literature.

This paper is related to two strands of research related to the economics of technology adoption. The first one analyzes the impact of digitization on total factor productivity. It is related to the productivity paradox debate, which refers to the global contraction in productivity growth rates, which occurred despite the spectacular technological progress observed in recent decades (Brynjolfsson, Rock, and Syverson 2017; Cusolito and Maloney 2018) . The second strand of research focuses on the creation (or destruction) of jobs brought about by technological change. It is related to the debate about the effects of digitization or robotization on job destruction and skill-biased labor demand (Autor 2015; Autor et al. 2020; Autor and Salomons 2018; Acemoglu and Restrepo 2018, 2019a, 2019b, 2020a, 2020b; World Development Report 2019)). These debates are related because job losses from technology adoption could result from firms' investments to become more efficient (Autor et al. 2020).

The rest of this paper is organized as follows. Section 2, briefly reviews the related literature. Section 3 describes the enterprise data used in the econometric estimations. Section 4 explains the estimation strategy. Section 5 validates the data and methodology by comparing our estimates with those in the existing literature. Section 6 presents the effects on productivity. Section 7 discusses the effects on factor demand. Since the estimation strategy is flexible, allowing for the estimation of a rich set of interactions between the lagged firm-choice variables and TFPR, Section 8 explores the issue of ICT program targeting by showing how the marginal impact of the adoption of digital tools depends on the other explanatory variables. The final section concludes.

2 Related Literature

As mentioned, this paper is related to two strands of the literature on technology adoption. One concerns the effect of adoption on productivity. The other is related to the impact of adoption on the demand for factors of production, particularly labor.

2.1 Productivity and Technology Adoption Literature

The productivity paradox debate has recently shifted its focus towards the contribution of digital-technology adoption to productivity. Estimates for developing countries are rare due to data limitations. Recent calculations for the United States show that the sector has been a bright spot in the economy, accounting for 6.5 percent of GDP and 3.9 percent of total employment in 2016 (Barefoot et al. 2018). The new estimates, which ranked the U.S. digital sector just below professional, scientific, and technical services, have encouraged some economists to argue that if the digital economy plays a limited role in advanced economies, we should not expect much for less developed economies, where digital services are less affordable and penetration rates lower.[2]

2. Early attempts to explain the productivity paradox have emphasized two hypotheses. The first one relates to the presence of diminishing returns from the digital revolution. Gordon (2015) argues that once firms adjust to the digital electronic wave, by installing new equipment or adopting new business practices, the impact of ICT technologies on productivity began to display diminishing returns. To complement this

In a recent influential paper on the United States, Brynjolfsson et al. (2020) argue that in the "discordance between high hopes and disappointing statistical realities, one of the two elements is presumed to be somehow wrong."[3] However, there are good reasons to be optimistic about the contribution of new technologies, including digital business solutions, to productivity and jobs. These technologies are general purpose technologies (GPTs) that have broad cross-sectoral applications (Jovanovic and Rousseau 2005; Helpman and Trajtenberg 1996). Brynjolfsson, Rock, and Syverson (2017), Syverson (2017), and Brynjolfsson et al. (2020) argue that GPTs have an impact in the economy after firms make the necessary complementary investments or organizational changes needed to take advantage of them. Yet the productivity gains from these investments or restructuring processes do not materialize immediately; it takes time to discover, develop, and implement them (Bresnahan, Brynjolfsson, and Hitt 2002).

Nonetheless, emerging evidence from advanced economies provides room for optimism. Recently, Gal et al. (2019) document that digital adoption in an industry is associated with productivity gains at the firm-level in 20 countries in the European Union and Turkey. Two earlier literature reviews by Syverson (2011) and Draca, Sadun, and Van Reenen (2006) concluded that there is a positive and significant association between ICT and productivity. These findings are, however, in contrast with recent evidence by DeStefano, Kneller, and Timmis (2018) for the United Kingdom, who show that ICT causes increases in firm size (captured by either sales or employment) but not productivity.

While evidence for developing countries is scarce, Hjort and Poulsen (2019) find positive effects of the arrival of internet on firm-level productivity in Africa. World Bank research on Argentina, Brazil, Chile, Colombia, and Mexico concludes that digital technology adoption

argument, (Bloom et al. 2020) document that it takes progressively more researchers to generate a unit of TFP. The second hypothesis is related to measurement issues associated with the supply of digital products or services for which the price paid by consumers is zero. Consequently, these transactions are not captured in the data (Mokyr 2014; Hatzius and Dawsey 2015; Byrne, Fernald, and Reinsdorf 2016). However, this hypothesis was challenged by evidence indicating that the size of the productivity slump was unrelated to the spread of digital technologies across countries (Syverson 2017).

3. Brynjolfsson, Rock, and Syverson (2017) refers to artificial intelligence, but the argument is equally applicable to other types of general purpose technologies such as digital technologies.

offers a pathway to higher productivity (Dutz, Almeida, and Packard 2018). According to the study, the total factor productivity of technology-adopting firms increased in all country studies where data were available, with the finding in Argentina based on labor productivity (Brambilla and Tortarolo 2018; Iacovone and Pereira-López 2018; Almeida et al. 2017; Dutz et al. 2017). However, systematic firm-level evidence for a large sample of developing countries was not available at the time of writing.

2.2 Jobs and Technology Literature

Recent technological innovations have also revamped an old concern related to the trade-off between efficiency and jobs. This debate is connected to the potential labor-saving and skill-biased effects of technology adoption (Brynjolfsson and McAfee 2014; Frey and Osborne 2017). Evidence about the effect of automation on jobs is primarily available for the United States in general equilibrium, as in Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018, 2019a), and the European Union (Autor and Salomons 2018). For example, Acemoglu and Autor (2011) explore the role of routinization of tasks due to the arrival of ICT technologies in job polarization. The article concludes that job polarization in the United States and the European Union is partly the result of the secular price decline in the real cost of information technologies. This is because routine tasks are characteristic of middle-skilled cognitive and manual jobs, which made them more vulnerable to the effects of technology adoption.

Recent evidence for the United States suggests that automation through the adoption of robotics can displace certain types of jobs (Acemoglu and Restrepo 2018). The estimates imply that one more robot per thousand workers reduces the employment-to-population ratio by about 0.2 percentage point and wages by 0.42 percent. In a follow-up paper, the authors explore the types of workers that have a higher probability of being replaced, concluding that robots primarily replace middle-aged workers between the ages of 21 and 55 (Acemoglu and Restrepo 2019b).

While evidence for developing countries is thin, the recent World Development Report (World Development Report 2019) shows that the variance of the labor-saving effect is so large that it is hard to conclude that robots will indeed decrease the net demand for labor. Furthermore, as highlighted by Acemoglu and Restrepo (2018, 2019a, 2019b), at the aggregate level, the job displacement effects will push wages down and help introduce new tasks that are labor-intensive.

Evidence about firm- and country-level job effects from technology adoption are only available for a handful of middle-income countries. A World Bank study (Dutz, Almeida, and Packard 2018), which summarizes findings for Argentina, Brazil, Colombia, Chile, and Mexico, shows that across these economies except Brazil, ICT adoption by firms is associated with increases in total employment and in employment of low-skilled labor (Brambilla and Tortarolo 2018; Dutz, Almeida, and Packard 2018; Iacovone and Pereira-López 2018; Almeida et al. 2017; Dutz et al. 2017). This paper advances the literature by providing evidence about the effect of digital-technology adoption on factor demand across a large sample of formal manufacturing enterprises in developing countries and by identifying the channels through which factor demand is affected. The two channels are factor-saving productivity improvements and scale effects, which reflects the impact of digital-technology adoption on a firm's customer base.

3 Data

The empirics rely on panel data of manufacturing firms from the World Bank Enterprise Survey Database (WBES). The estimation sample covers 82 countries from a maximum sample of 90 countries in the six regions where the World Bank operates: Europe and Central Asia - ECA (30), Sub-Saharan Africa - SSA (27), Latin America and the Caribbean - LAC (18), East Asia and Pacific - EAP (6), South Asia - SA (6), and Middle East and North Africa - MENA (3).

The survey is nationally representative of the formal private sector. It is built based on a stratified random sampling frame designed by the WBES team. Three variables are used to construct the strata: firm size, sector, and geographic area within a country. Under the WBES sampling framework, firms are divided into three categories according to their size: small, medium-sized, and large. Small firms are those with 5-19 full-time employees; medium-sized firms have 20-99 full-time employees; and the large ones have more than 99 full-time employees. The industries are classified according to the ISIC Revision 3.1 classification at 2-digits. The regions within a country are defined by the WBES team. The database also includes sampling weights that can be used to mimic nationally representative samples in the empirics.

The WBES collects data on a broad range of variables related to firm production, performance, and the business environment in which firms operate. It has information on variables related to production such as sales, capital, labor, materials, investment, exports, and manager's education, among others. Due to the lack of information on prices at the firm-level, we use the consumer price index from the World Bank's World Development Indicators to deflate sales, capital, materials, and investment, thus transforming nominal values into 2010-dollar values. Firms' labor is equal to the number of permanent employees that work for the firm. The survey collects data on the percentage of firms' sales that are exported. Last, a firm's managerial capability is measured by the number of years of experience of the manager. The novelty of the WBES is that it also collects information on technology adoption at the firm-level. Thus, at every wave, firms are asked whether they use a business email to communicate with clients and suppliers and whether they have a business website in order to carry out their operations. We exploit this variation in time, across countries, sectors, and firms to estimate the effects of digital business solutions on productivity and factor demand.

To construct the estimation sample, we first compiled all the WBES waves available from 2002-2019. This creates a sample of 145,626 observations, which corresponds to 118,868 firms, operating in the manufacturing or service industries. Table 6 in section A of the Appendix provides detailed information about this sample across countries and years. After this, we drop firms for which we cannot identify the sector in which they operate. This give us a sample of 131,347 observations.

If we further restrict this sample to manufacturing industries, which is the focus of our analysis, we end up with a sample of 74,723 observations corresponding to 59,820 firms. Of these firms, 79.4 percent appear only once in the database; 17.0 percent appear twice; 3.0 percent appear three times; 0.5 percent appear four times; and 0.1 percent appear five times. Table 7 in section A of the Appendix displays detailed information about this sample across countries and years.

A common feature of many firm-level databases from developing countries is the presence of missing values for variables needed to measure firm performance (e.g., labor, sales, capital, and materials, and investment). For example, in our sample, labor is the variable with the least proportion of missing values (2.3 percent), followed by sales (14.2 percent), materials (31.8 percent), capital (32.8 percent), and investment (58.2 percent).

To maximize sample size, correct selection in misreporting, and gain efficiency, we impute data for sales, labor, capital, materials, and investment using the largest WBES database available, which contains 131,347 observations, and a pseudo-Gibbs sampler (Lee and Carlin 2010; Van Buuren, Boshuizen, and Knook 1999).[4] The explanatory variables used for imputation include email adoption, website adoption, export status, managerial experience proxied by a dummy variable that identifies firms with managers with above-median years of experience. It also controls for country, industry, and survey year. We do not impute data for email adoption, website adoption, export status, and managerial experience as we are interested in understanding their effect on TFPR. Table 8 in section A of the Appendix presents summary statistics of the main variables with and without imputation. As can be observed, the imputation method performs well, as there are not statistically significant differences in the statistics across sample groups.

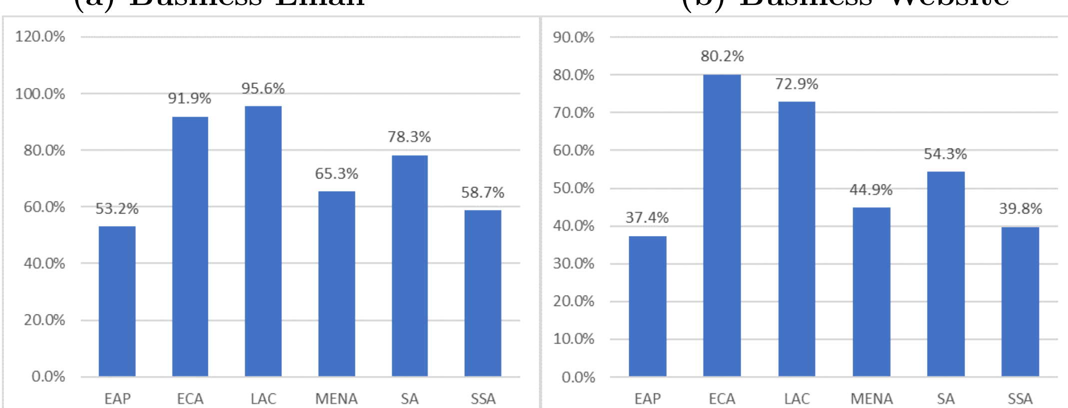
4. The only observations that were not included in the imputation method were those that did not report any sector activity.

To construct the estimation panel database, we drop all firms that have a missing value in at least one of the variables used in the analysis (e.g., email, website, exports, management, sales, capital, materials, labor, and investment). In turn, we eliminate all the firms with information only for one wave and we keep industries that have at least 250 observations, as this is the minimum sample size we used to estimate TFPR at the sectoral level. Table 9 in section A of the Appendix presents descriptive statistics corresponding to the variables used to estimate TFPR using the estimation sample.

Figure 3.1 displays GDP-weighted regional average email (panel a) and website (panel b) adoption rates using the last wave of the WBES data for each country included in the sample. It includes 26 countries from ECA, 26 from SSA, 16 from LAC, 6 from SA, 5 from EAP, and 3 from MENA. These adoption rates are not fully comparable across regions, as the WBES team collects information for different countries at several points in time. As Table 6 shows, the timing corresponding to the last wave of the WBES varies across regions. It is 2015-2016 for the EAP region; 2012-2013 for the ECA region; 2009-2017 for LAC; 2007-2016 for MENA; 2013-2015 for SA; and 2007-2018 for SSA.

Figure 3.1: **Regional Adoption Rates**

(a) Business Email **(b) Business Website**



Note: Panel a and Panel b of Figure 3.1 display the GDP-weighted regional average email and website adoption rates corresponding to the last wave of the WBES database for each of the countries included in the panel database, respectively. The rates consider sampling weights and therefore, they are representative at the national level. However, adoption rates are not fully comparable across regions, as the World Bank collects the data at different points in time. As Table 6 shows, the timing corresponding to the last wave of the WBES varies across regions. The timing corresponding to the last wave of the WBES varies across regions. It is 2015-2016 for the EAP region; 2012-2013 for the ECA region; 2009-2017 for LAC; 2007-2016 for MENA; 2013-2015 for SA; and 2007-2018 for SSA. The region and country composition of the sample is as follows: Europe and Central Asia - ECA (26 countries), Sub-Saharan Africa - SSA (26 countries), Latin America and the Caribbean - LAC (16 countries), South Asia - SA (6 countries), East Asia and Pacific - EAP (5 countries), and Middle East and North Africa - MENA (3 countries).

4 Methodology

The estimation strategy proceeds in two stages. The first focuses on the estimation of TFPR; the second on the estimation of factor demand.

4.1 Estimating the productivity premium from digital-technology adoption

The productivity variable to be estimated is revenue-based total factor productivity (TFPR). We estimate this measure, instead of physical TFP, because the WBES does not collect information on prices. Thus, in order to construct proxy variables for output and inputs in comparable units across countries and over time, we use country deflators like the consumer price index. Our measure of TFPR thus captures variations in prices and efficiency. It is therefore a measure of firm profitability.

To estimate TFPR, we first estimate a log-linearized Cobb-Douglas production function (PF), assuming that the PF elasticities vary at the 2-digit sector level. The estimation method follows Ackerberg, Caves, and Frazer (2015), who rely on the control function approach (CFA) to allow for endogeneity of factor choices and materials usage to make productivity observable. Since the WBES follows a sub-sample of firms interviewed to construct the panel, the data do not capture firm entry-exit dynamics. As a result, we could not control for selection in factor choices and materials usage.

While the Ackerberg, Caves, and Frazer (2015) method assumes an exogenous productivity process, we follow De Loecker (2013) and endogenize it. Thus, in our specification, TFPR is a function of the adoption of digital business solutions (e.g., email and website) as well as exporting status and managerial experience. Assuming an exogenous TFPR process, by contrast, would have implied that digital business solutions would have no impact on efficiency or sales. This is not only unrealistic, but also would have invalidated the moment conditions needed to identify the coefficients of the production function, as the productivity shock would not have been orthogonal to factor choices. In other words, if TFPR is a function of digitization, the PF elasticities will be biased. The sign of the bias is ambiguous, depending on whether digitization is factor-augmenting or factor-saving. If business digitization is factor-augmenting, then TFPR would be underestimated. By contrast, if TFPR is factor-saving, TFPR will be overestimated.

There are important reasons to make TFPR a function of business digitization. Using email to connect with clients and suppliers or having a business website to gain online presence can affect TFPR through various channels. On the demand-side of the market for an enterprise's goods and services, reductions in search and transaction costs affect firm profitability at the extensive and intensive margins, by facilitating access to new clients or expanding the volume of transactions online. Dynamically, the scale-up of the demand for a firm's products or services increases profits, allowing it to pay the fixed cost of investing in TFPR-enhancing activities like innovation, managerial upgrading, or technology adoption (Bustos 2011). On the supply-side, using email to connect with suppliers helps improve production efficiency, by enlarging the potential set of input providers in non-relationship specific investments. Alternatively, it reduces the number of suppliers in relationship-specific investments but enlarges the fraction of repeated interactions, thus addressing contract incompleteness and guaranteeing access to specific assets needed to produce more sophisticated goods (Aral, Bakos, and Brynjolfsson 2018). Because adoption of digital business solutions is not exogenous, we lagged the corresponding variables used to estimate their effects on TFPR.

Since WBES data are not census data, a key question is whether to do weighted estimations by using sampling weights to estimate the coefficients of the production function and TFPR. Following Cameron and Trivedi (2005), sampling schemes such as stratification lead to the conditional density of any variable in the sample differing from that in the population.

However, if stratification is purely exogenous, such that it does not take into consideration the dependent variable to stratify the sample, then the estimated parameters are consistent, regardless of differences between the estimation sample and the true underlying population. By contrast, under pure endogenous sampling, the marginal distribution of the dependent variable in the sample differs from that in the population, and as a result, the estimated coefficients are inconsistent. Since firms' sales have not been used to stratify the WBES, we do not use country-specific weights for the estimation of the coefficients of the PF. Last, following the literature on PF estimation using the CFA, we bootstrapped the standard errors using 100 replications and country and year to construct the strata.

After estimating the PF elasticities, we use equation 4.1 to estimate TFPR. Then, with unbiased estimates of TFPR at the firm-level in hand, we pool all the observations and run an OLS regression of unbiased-TFPR on digital business solutions (e.g., email and website) to estimate the marginal effects of digitization on TFPR. The OLS coefficients are mathematically equivalent to the weighted average of the estimated coefficients obtained from the PF estimation, where the Markov coefficients vary at the sector-level (see Appendix B for the proof).

We assume homogeneous effects of digital-technology adoption on TFPR (instead of sector effects) for two reasons. First, the type of digitization we are interested in falls under the category of general-purpose technologies (instead of sector-specific technologies). The second reason is to gain efficiency and increase the degrees of freedom in the estimation, as several sectors have few observations once we lagged the explanatory variables used to endogenize TFPR to control for endogeneity. Provided we focus the interpretation of the results (inference) on the entire sample, our approach eliminates imprecisions coming from making estimations with small sub-samples.

Our empirical strategy has three stages. Stages 1 and 2 are the standard Control Function Approach stages, with the difference that we extend Ackerberg, Caves, and Frazer (2015) and De Loecker (2013) and endogenize TFPR as a function of four firm-choice variables, including the adoption of digital tools (website and email), exporting status and managerial experience. In the third stage, we recover the weighted average email and website marginal effects on TFPR at the firm-level. The following sub-sections provide further details about the specifications estimated in each stage.

4.1.1 TFPR estimation: First stage of the CFA

We first estimate a log-linearized Cobb-Douglas production function at the sectoral level:

$$\ln (Y_{ijct}) = a_j + b_j \ln (L_{ijct}) + c_j \ln (K_{ijct}) + d_j \ln (M_{ijct}) + \ln (TFPR_{ijct}) + D_c + D_t + e_{ijt}, \quad (4.1)$$

Y_{ijct}, L_{ijct}, K_{ijct}, and M_{ijct} refer to output, labor, capital, and materials used by firm i, which operates in sector j of country c, at time t. e_{ijct} is an i.i.d error term that captures unanticipated shocks to production or measurement error. D_c and D_t are country fixed-effects and time fixed-effects, respectively. Since productivity, $TFPR_{ijct}$, is unobservable, we follow Ackerberg, Caves, and Frazer (2015) and use materials to make it observable:

$$\ln (M_{ijct}) = h\left(\ln (L_{ijct}),\ \ln (K_{ijct}),\ \ln (TFPR_{ijct}),\ Email_{ijct},\ Website_{ijct},\ X_{ijct},\ D_c,\ D_t\right), \quad (4.2)$$

where X_{ijct} is the set of control variables that can affect TFPR (e.g., exporting status, managerial experience). Since materials are a strictly monotonic function of TFPR, we can invert function $h(\cdot)$, and express TFPR as a function of labor, capital, materials, digital business solutions and other determinants of firm performance:

$$\ln (TFPR_{ijct}) = h^{-1}\left(\ln (L_{ijct}),\ \ln (K_{ijct}),\ \ln (M_{ijct}),\ Email_{ijct},\ Website_{ijct},\ X_{ijct},\ D_c,\ D_t\right). \quad (4.3)$$

Inserting equation (4.3) into (4.1) yields:

$$\ln(Y_{ijct}) = a_j + b_j \ln(L_{ijct}) + c_j \ln(K_{ijct}) + d_j \ln(M_{ijct}) \tag{4.4}$$
$$+ h^{-1}\left(\ln(L_{ijct}),\ \ln(K_{ijct}),\ \ln(M_{ijct}),\ Email_{ijct},\ Website_{ijct},\ X_{ijct},\ D_c,\ D_t\right) + D_c + D_t + e_{ijt}.$$

Equation (4.4) can be estimated by OLS. We approximate function $h(\cdot)$ using a third degree polynomial on labor, capital, and materials. Following Ackerberg, Caves, and Frazer (2015), in the first step we cannot identify the coefficients of the PF. However, we can remove the estimated error term, and use output minus its predicted value to estimate the TFPR process and use the productivity shock for the moment conditions used to estimate the elasticities of the PF.

4.1.2 TFPR estimation: Second stage of the CFA

As mentioned, the Ackerberg, Caves, and Frazer (2015) CFA relies on an exogenous Markovian TFPR process to estimate the PF elasticities:

$$\ln(TFPR_{ijct}) = g\left(\ln(TFPR_{ijct-1})\right) + \varepsilon_{ijct} \tag{4.5}$$

Following De Loecker (2013), the standard CFA can be extended by endogenizing TFPR as a function of digital business solutions, or any firm choice variable. Moreover, we adopt a flexible functional approach, which allows the marginal effects of digital business solutions to vary with a firm's initial level of TFPR. Formally, to control for the endogeneity of email and website adoption, we lagged these variables, as well as those included in X_{ijct}. The resulting estimation equation is:

$$\ln(TFPR_{ijct}) = \alpha_j + \rho_{j1} \ln(TFPR_{ijct-1}) + \rho_{j2} \ln(TFPR_{ijct-1})^2 + \rho_{j2} \ln(TFPR_{ijct-1})^3 \tag{4.6}$$
$$+ \Psi\left(Email_{ijct-1},\ Website_{ijct-1},\ Export_{ijct-1}\ Managerial_{ijct-1}\right) + D_c + D_t + \varepsilon_{ijct},$$

where Ψ is a function that includes $Email_{ijct-1}$,$Website_{ijct-1}$, $Export_{ijct-1}$, and $Managerial_{ijct-1}$ as free-standing variables, as well as all the possible interaction terms with all the arguments of function Ψ. The term ε_{ijct} is by assumption uncorrelated with any lagged choice variable because the latter are in the firm's information set. This forms the basis for the identification of the labor, capital, and material elasticities in the final stage of the Ackerberg, Caves, and Frazer (2015) procedure. Thus, the PF elasticities are estimated using the following moment conditions:

$$E\left[\varepsilon_{ijct}\left(b_{jc},\ c_{jc},\ d_{jc}\right)\begin{pmatrix}\ln\left(L_{ijct-1}\right)\\ \ln\left(K_{ijct-1}\right)\\ \ln\left(M_{ijct-1}\right)\end{pmatrix}\right]=0. \tag{4.7}$$

The Ackerberg, Caves, and Frazer (2015) approach uses a value-added (instead of output) PF to estimate TFPR. It is intentionally done in this way to avoid estimating the elasticity corresponding to materials and therefore address the concern that lagged materials is not a valid instrument. Bond and Söderbom (2005) argue that materials are a flexible input, which implies that it does not follow an auto-regressive process. To explore this issue, we estimated an AR (1) model for materials and found that it is equal to 0.86. We prefer this approach instead of the value-added approach, as the latter implicitly assumes an output elasticity with respect to materials equal to 1. The coefficients of the production functions are thus estimated by minimizing the sample analogue of equation (4.7) using GMM.

4.1.3 TFPR estimation: Estimating global average digital business solution marginal effects

With unbiased estimates of TFPR in hand, we pool all the observations and estimate equation (4.6) using OLS. Appendix B shows that the estimated coefficients in the whole sample are a weighted average of the coefficients obtained across subsamples.

4.2 Estimating the Effects on Labor and Capital Demand

Recent technological innovations have revamped an old concern about productivity-driven displacement of jobs and shifts of labor demand towards skilled workers. New theoretical models developed to understand the potential effects of automation on jobs, as well as the channels through which it operates, depart from the standard factor-augmenting technological change approach. Instead, they propose a new framework, where robots compete against workers, and thus machines replace tasks previously performed by humans (Acemoglu and Restrepo 2018, 2019b, 2020a; Autor and Salomons 2018). However, the displacement-induced contraction in wages dynamically creates incentives for the introduction of new tasks, in general equilibrium, where labor has a comparative advantage relative to technology, the so-called reinstatement effect. This new setup thus enables researchers to think about new forces at work, which have opposing effects on labor demand in general equilibrium.

Our estimation framework with enterprise panel data is, by definition, partial equilibrium. But the estimation framework is flexible and allows for the estimation of the effects of the choice variables on both TFPR and factor demand. As mentioned, the latter effect has two channels, the factor-augmenting or saving effect as well as a scale effect. This allows for a direct test of labor- (and capital-) saving hypothesis. Since our TFPR measure confounds both prices and efficiency, our productivity-driven effect is not fully comparable to the displacement effect cited in the literature (Acemoglu and Restrepo 2018, 2019a). This is because the price-related component of this effect could be labor-augmenting, as efficiency gains are passed-through onto product prices. That is, efficiency gains resulting in price reductions can increase product demand. The efficiency-related component of this effect could be labor-saving, just like the displacement effect cited in the literature. The scale effect, however, is unambiguously labor-augmenting. It is associated with an expansion in firms' profits due to a reduction in marginal costs or the scale-up of demand for a firm's output as digitization allows firms to reach a larger potential customer base. Thus, to estimate the factor demand effects from digitization (as well as that of exporting and managerial experience), we estimate the following equation:

$$\Delta \ln (FP_{ijc}) = \theta_1 + \theta_2 \Delta Email_{ijc} + \theta_3 \Delta Website_{ijc} + \theta_4 \Delta \ln (TFPR_{ijc}) \\ + \theta_5 \Delta X_{ijc} + D_c + D_j + D_t + \upsilon_{ijc}, \tag{4.8}$$

where $\Delta \ln (FP_{ijc})$ stands for changes in the use of factors of production, labor and capital.

5 Data and Estimation Validation

To validate the estimations of the effect of digital technology adoption on TFPR when applied to the WBES database, we estimate the same specification as the baseline specification reported in De Loecker (2013), which relies on data from Slovenia. This involves the estimation of a value-added Cobb-Douglas production function on labor, capital, and productivity, where the latter is assumed to be an endogenous process of learning by exporting. Table 1 presents the results from the production function elasticities, while Table 2 displays the median learning-by-exporting effects on TFPR.

Table 1: WEBS-De Loecker Comparison: Production Function Elasticities

Sector Description	WBES			De Loecker		
	L	K	K/L	L	K	K/L
Food & beverages	0.933	0.241	0.258	0.810	0.131	0.162
Textiles	0.925	0.206	0.223	0.562	0.165	0.294
Garments	0.911	0.251	0.276	0.833	0.152	0.182
Leather	0.735	0.364	0.495	0.542	0.356	0.657
Wood	0.868	0.160	0.184	0.885	0.063	0.071
Publishing, printing and reproduction	0.978	0.262	0.268	0.603	0.337	0.559
Chemicals	1.038	0.205	0.197	0.601	0.274	0.456
Rubber & plastics	1.071	0.204	0.190	0.669	0.142	0.212
Other non-metallic products	0.974	0.254	0.261	0.614	0.255	0.415
Basic metals	1.202	0.198	0.165	0.751	0.042	0.056
Fabricated metal prods.	1.097	0.184	0.168	0.666	0.194	0.291
Machinery and equipment	0.991	0.225	0.227	0.700	0.199	0.284
Electrical machinery	1.102	0.230	0.209	0.558	0.223	0.400
Furniture	0.877	0.307	0.350	0.709	0.146	0.206

Notes. Table 1 presents the production function elasticities from estimating a value-added log-linearized Cobb-Douglas production function following De Loecker (2013). In this paper, value-added is a function of labor and capital. The estimating method is based on the Control Function approach by Ackerberg, Caves, and Frazer (2015). However, it departures from the latter by assuming an endogenous Markovian productivity process, which is a function of learning by exporting. WBES data covers a sample of 7,916 manufacturing enterprises from 82 developing countries during the period 2002-2019; while De Loecker (2013) study focuses on 7,915 manufacturing firms in Slovenia during the period 1994-2000. Data for WBES come from the World Bank, while data fromDe Loecker (2013) come from the Slovenian Central Statistical Office. The correlation coefficient between the K-to-L estimated ratio using the WBES and De Loecker (2013) database is 0.55. It is also statistically significant at the 5 percent level.

Using the production function elasticities from Table 1, we calculate sector-specific factor intensities, defined as the capital-to-labor PF elasticity ratio, and examine the pairwise correlations between the results obtained using the WBES database and those from De Loecker (2013). We found a correlation coefficient of 0.55 between factor intensities, which is significant at the 5 percent level. The correlation coefficient between median productivity-premium from exporting is 0.36. This is high given that we only have 15 observations and there is a lot of cross-country variation in the WBES database.

Table 2: WBES-De Loecker Comparison: Non-Parametric Estimates of Exporting on TFPR (in percent)

Sector Description	Median Productivity Premium from Exporting	
	WBES	De Loecker
Food & beverages	5.953	2.280
Textiles	4.949	1.980
Garments	3.696	1.660
Leather	-1.577	1.830
Wood	7.186	1.920
Publishing, printing and reproduction	5.732	4.880
Chemicals	6.541	3.930
Rubber & plastics	6.122	4.500
Other non-metallic products	5.246	2.730
Basic metals	5.141	3.190
Fabricated metal products	6.071	3.320
Machinery and equipment	4.218	3.450
Electrical machinery	3.687	4.640
Furniture	1.862	1.990

Note: Table 2 presents the median TFPR-premium from exporting following De Loecker (2013) method. The latter is based on the estimation of a value-added log-linearized Cobb-Douglas production function based on the Control Function approach by Ackerberg, Caves, and Frazer (2015) and assuming an endogenous (cubic) Markovian (AR 1) productivity process, which is a function of learning by exporting. WBES data covers a sample of manufacturing enterprises from 82 developing countries during the period 2002-2019; while De Loecker (2013) study focuses on 7,915 manufacturing firms in Slovenia during the period 1994-2000. Data for WBES come from the World Bank, while data from De Loecker (2013) come from the Slovenian Central Statistical Office. The correlation coefficient is 0.36.

6 Nonparametric Estimates of the Digital-Technology Adoption Effect (DAE) on TFPR

This section presents the semi-parametric estimates of the digital adoption effects (e.g., email and website), using the approach presented in section 4. Table 3 reports the median effects, the percentage of the estimation sample with positive marginal effects, and the F-test associated with each variable of interest. Column (1) displays the results from estimating an endogenous TFPR process that is a function of learning by exporting, as in De Loecker (2013). Column (2) reports the results from estimating an endogenous TFPR process that is a function of the adoption of digital business solutions, namely email and website. Column

(3) presents the results from estimating an endogenous TFPR process that is a function of managerial experience. Column (4) shows the most complete specification that includes four choice variables, business web site, business email, exporting, and managerial-experience effects.

Column (1) reports a probability-adjusted expected median productivity premium from exporting of 1.68 percent, with the entire sample of firms displaying positive marginal effects from exporting. This is calculated as the sample probability of becoming an exporter times the estimated marginal productivity effect (0.3 times 0.056). As in De Loecker (2013), we reject the null hypothesis of an exogenous productivity process, in favor of a specification with learning by exporting effects. Column (2) shows a positive productivity premium from email adoption for almost 50 percent of the estimation sample. The probability-adjusted premium is almost negligible. The probability-adjusted median TFPR-premium from website adoption is also close to zero, with 22.57 percent of the estimation sample showing a positive impact. The large proportion of firms displaying negative marginal effects could mirror the same measurement problem associated with estimating the effects of process innovation on productivity. If innovation (in this case digital technology adoption) is cost saving and the demand for the good a firm sells is not sufficiently price responsive, then TFPR can decrease when digitization-triggered cost reductions are passed-through onto prices (see the literature review by Hall and Monhen (2013)). As with the first specification, we reject an exogenous productivity process in favor of a specification, where digital technology adoption affects firm performance. Column (3) shows a positive managerial-experience premium for all firms with more educated managers. The median premium effect is 0 percent and the F-test rejects an exogenous TFPR process. However, these three model specifications can yield biased estimates because they omit the other firm-choice variables. Therefore, our preferred specification reported under column 4 includes all four choice variables simultaneously.

Table 3: Estimated Median Productivity Premium: Digital-Technology Adoption, Learning by Exporting, and Managerial Experience

Productivity Determinants	(log)-Productivity Premium	Endogenous Markov Specification (1)	(2)	(3)	(4)	Probability-adjusted Effects (1)	(2)	(3)	(4)
Exporting status	Median TFPR Effect (MPE)	0.056			0.036	0.0168			0.0168
	% of obs. with MPE >0	100			59.4	100			59.4
	F-test	4.362***			8.193***	4.362***			8.193***
Email Adoption	Median TFPR Effect (MPE)		-0.001		0.015		-0.0007		0.010
	% of obs. with MPE >0		49.538		67.3		49.538		67.3
	F-test		9.685***		5.629***		9.685***		5.629***
Website Adoption	Median TFPR Effect (MPE)		-0.057		0.044		-0.00285		0.022
	% of obs. with MPE >0		22.578		54.6		22.578		54.6
	F-test		4.882***		3.246**		4.882***		3.246**
Managerial Experience	Median TFPR Effect (MPE)			0.001	0.001			0.0005	0.0005
	% of obs. with MPE >0			83.0	60.6			83.0	60.6
	F-test			2.26*	7.493***			2.26*	7.493***
R^2		0.877	0.886	0.890	0.887	0.877	0.886	0.890	0.887
F-Total			11.753***		6.77***		11.753***		6.77***
N					7,916				

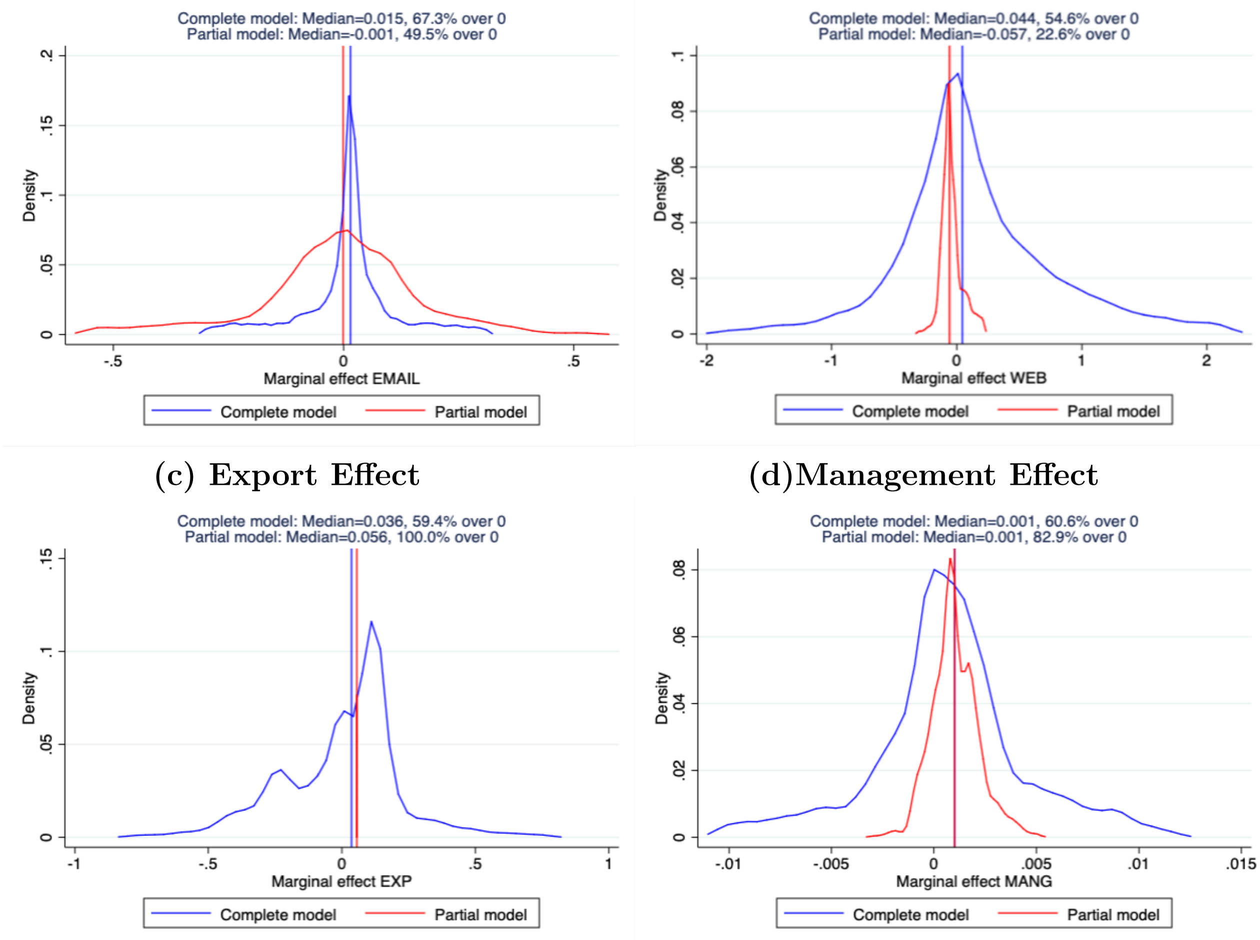
Note: Table 3 presents the results from estimating equation 4.6 using the Control Function approach by Ackerberg, Caves, and Frazer (2015) and endogenizing the (cubic) Markovian (AR 1) productivity process to make it a function of digital-technology adoption, learning by exporting, and managerial experience. The estimated marginal effects represent weighted average of the effects estimated at the sectorial level. Thus, the pool specification used to recover the coefficients from equation 4.6 controls for sector, country, and time fixed effects. Productivity determinants have been instrumented with a one-period lag to control for endogeneity. Standard errors have been bootstrapped using 100 replications and country-year strata. The F-statistics are used to evaluate the null hypothesis of an exogenous productivity process against an alternative hypothesis of an endogenous process. The "exporting status" takes value 1 if the firm sells a product in international markets; "email adoption" takes value 1 if the firm uses email to connect with clients and suppliers; "website adoption" takes value 1 if the firm has a business website; "managerial experience" is measured by number of years of experience of the manger.The reported effect of experience is for firms with managers with above median years of experience (17 years). Outliers were removed after the productivity premium effects were calculated. We define outliers those observations whose corresponding productivity premiums is higher than "U" or lower than "L", where U is defined as the first quartile minus 2.5 times the interquartile range (IQR) and L is defined as the third quartile plus 2.5 times IQR.

The results of the preferred model indicate that the omission of any of these variables changes the results. Figure 6.1 displays the corresponding kernel densities for the TFPR-premium associated with email adoption (panel a), website adoption (panel b), learning by exporting (panel c), and accumulation of managerial experience (panel d) after removing outliers. There are two kernels in each panel. One represents the distribution of the TFPR-premium for the partial model and the other one for the complete model. The (log)TFP-premiums are positive for 67.3 (email adoption), 54.6 (website adoption), 59.4 (learning by exporting), and 60.6 (managerial experience) percent of the estimation sample, respectively. The probability-adjusted median TFPR-premium associated with email adoption is 1.6 percent and that of website adoption is 2.2 percent. The probability-adjusted median TFPR-premium from getting access to external markets is 1.6 percent, while that of increasing the years of experience of the manager is near zero.

Figure 6.1: **Estimated Digitization, Exporting and Management TFPR-Premium**

(a) Email Effect **(b) Website Effect**

(c) Export Effect **(d)Management Effect**



Note: Figure 6.1 displays the marginal effects from digitization, learning by exporting, and accumulation of managerial experience that result from estimating the econometric model displayed in equations 4.1-4.7. The corresponding specification assumes an endogenous productivity process that it is a function of digital-technology adoption (email and website), learning by exporting, and accumulation of managerial experience above the country-median. The panels in figure 6.1 display the marginal effects for the estimation sample removing outliers. Outliers were removed after the productivity premium effects were calculated. We define outliers those observations whose corresponding productivity premiums is higher than "U" or lower than "L", where U is defined as the first quartile minus 2.5 times the interquartile range (IQR) and L is defined as the third quartile plus 2.5 times IQR. Variable "EXP" takes value 1 if the firm sells a product in international markets; "EMAIL" takes value 1 if the firm uses email to connect with clients and suppliers; "WEB" takes value 1 if the firm has a business website; "MANG" is the log of the number of years of experience of the manager.

7 Estimates of the Digital Technology Adoption Effects on Jobs and Capital

The objectives of this section are to quantify the effects of digitization, both email and website adoption, on factor demand (labor and capital) and identify the channels through which they operate. As discussed in the methodological section, we work with a specification that assumes two different channels: (i) a productivity-driven effect and (ii) a scale effect. Since our TFPR measure confounds both prices and efficiency, our productivity-driven effect is not fully comparable to the displacement effect cited in the literature (Acemoglu and Restrepo 2018, 2019b). This is because the price-related component of this effect could be labor-augmenting if the efficiency gains are passed-through onto prices, and the price reduction can increase product demand. The scale effect is labor-augmenting. It is associated with an expansion in firms' profits due to a reduction in marginal costs or the scale-up of demand as digitization allows firms to reach a larger potential customer base.

7.1 Effects on Jobs

Table 4 presents the results from estimating equation 4.8, the effects of digital-technology adoption on jobs, for each of the endogenous TFPR specifications we estimated in the previous section (Table 3 columns 1-4). Unfortunately, due to WBES limitations in questionnaire design, we cannot measure the impact of digital-technology adoption on the skill composition of labor in a straightforward manner, especially across regions. This is because there are discrepancies in the questionnaires across countries and time. For example, while some surveys collect information on high-school education, others do it for college graduates. Further, the type of information collected is not independent of the level of development of the country. The WBES questionnaires for upper middle-income countries focus on college graduates, whereas those for low-income countries collect information on the share of high-school graduates. Column (1) displays estimated labor-demand effects, when assuming an endogenous TFPR process that is a function of learning by exporting. Column (2) excludes exporting effects and assumes an endogenous TFPR process that is a function of digitization. Column (3) assumes an endogenous TFPR process that is a function of managerial experience. The most complete specification is the one displayed in Column (4), which shows the effects of changes in digitization, learning by exporting, and accumulation of managerial experience on labor demand.

Table 4: Estimates of the Digital-Technology Adoption Effects on Jobs

Variable of Interest		WBES			
		(1)	(2)	(3)	(4)
Change in Export Status	Coeff.	0.341			0.303
	St.Dev	(0.082)			(0.066)
	T-test	[4.167]			[4.578]
Change in Email Adoption	Coeff.		0.240		0.220
	St.Dev		(0.077)		(0.068)
	T-test		[3.109]		[3.212]
Change in Website Adoption	Coeff.		0.227		0.215
	St.Dev		(0.046)		(0.040)
	T-test		[4.919]		[5.418]
Change in Manager's experience	Coeff.			-0.539	0.004
	St.Dev			(0.175)	(0.001)
	T-test			[3.074]	[2.981]
Change in TFPR	Coeff.	0.083	0.062		0.034
	St.Dev	(0.022)	(0.021)		(0.015)
	T-test	[3.841]	[2.955]		[2.293]
R^2		0.073	0.081	0.053	0.105
N		7,926			

Note: Table 4 presents the results from estimating equation 4.8 for the pool sample. For each of the estimated specifications, we use changes in estimated TFPR assuming the same corresponding specification as in Table 3. The estimation controls for sector, country, and time fixed effects. The "exporting status" takes value 1 if the firm sells a product in international markets; "email adoption" takes value 1 if the firm uses email to connect with clients and suppliers; "website adoption" takes value 1 if the firm has a business website; "managerial experience" takes value 1 if the firm has a manager with years of experience above the country-median. "Employment" measures full-time employees; "Exporting status" takes value 1 if the firm sells a product in international markets; "Email adoption" takes value 1 if the firm uses email to connect with clients and suppliers; "Website adoption" takes value 1 if the firm has a business website; "Manager's experience" takes value 1 if the firm has a manager with years of experience above the country-median.

Table 4 shows that changes in digital-technology adoption, exporting, and accumulation of managerial experience have positive and statistically significant effects on jobs. For our preferred specification, which is the one displayed in Column 4, the largest effect comes from exporting (30 percent, approximately), followed by digitization (21 percent for each variable), and managerial experience (0.1 percent). Interestingly, in all the specifications, the TFPR-related effect is positive and statistically significant, meaning that TFPR improvements are labor-augmenting. However, this does not necessarily means that the effect is positive for all the sectors, as Table 3 displays pooled regressions, which are a weighted-average of the sector-specific ones. Sector-specific regressions, which are available upon request, show that the positive TFPR effect is mainly explained by sectors like garments and fabricated metals. This contrasts with other sectors such as chemicals, where the estimated effects are negative.

7.2 Effects on Capital

Table 5 reports the results for demand for capital. For the variable of interest, the results are similar to those reported in Table 4. That is, changes in digital-technology adoption, (both email and website), exporting status, and managerial experience have a positive and statistically significant effect on changes in the demand for capital. The largest effect is observed for email adoption (57 percent), followed by exporting (35 percent), and website adoption (17 percent, approximately) (Table 4, column 4). In contrast, changes in TFPR have no statistically significant effect in any specification.

Table 5: Estimates of the Digital-Technology Adoption Effects on Capital

Variable of Interest		WBES			
		(1)	(2)	(3)	(4)
Change in Export Status	Coeff.	0.418			0.349
	St.Dev	(0.115)			(0.103)
	T-test	[3.623]			[3.380]
Change in Email Adoption	Coeff.		0.594		0.566
	St.Dev		(0.137)		(0.131)
	T-test		[4.340]		[4.322]
Change in Website Adoption	Coeff.		0.207		0.171
	St.Dev		(0.065)		(0.062)
	T-test		[3.199]		[2.736]
Change in Manager's experience	Coeff.			0.009	0.008
	St.Dev			(0.004)	(0.003)
	T-test			[2.498]	[2.425]
Change in TFPR	Coeff.	-0.003	-0.026	0.009	0.074
	St.Dev	(0.076)	(0.075)	(0.076)	(0.05)
	T-test	[0.045]	[0.346]	[0.120]	[1.488]
R^2		0.254	0.266	0.252	0.265
N		7,926			

Note: Table 5 presents the results from estimating equation 4.8 for the pool sample. For each of the estimated specifications, we use changes in estimated TFPR assuming the same corresponding specification as in Table 3. The estimation controls for sector, country, and time fixed effects. The "exporting status" takes value 1 if the firm sells a product in international markets; "email adoption" takes value 1 if the firm uses email to connect with clients and suppliers; "website adoption" takes value 1 if the firm has a business website; "managerial experience" takes value 1 if the firm has a manager with years of experience above the country-median. "Capital" measures the replacement value of the firm's assets; "Exporting status" takes value 1 if the firm sells a product in international markets; "Email adoption" takes value 1 if the firm uses email to connect with clients and suppliers; "Website adoption" takes value 1 if the firm has a business website; "Manager's experience" takes value 1 if the firm has a manager with years of experience above the country-median.

8 Program Targeting and Complementarities among TFPR-Enhancing Investments

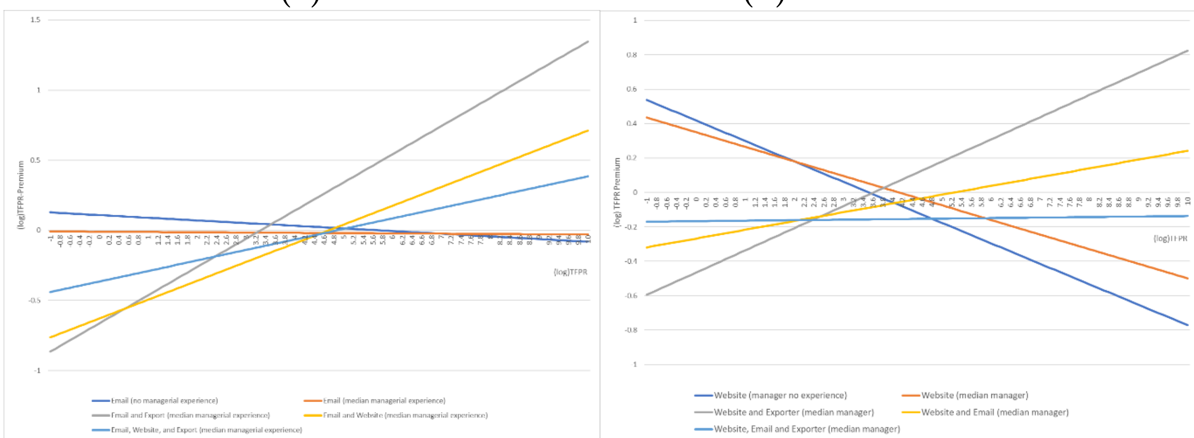
A fundamental question that emerges from the analysis is how governments can use the previous findings to guide the design of public programs aimed at fostering digital-technology adoption. Governments are often concerned with "targeting": that is, identifying the types of firms that can benefit the most from a specific policy. Targeting is important when public resources are limited. Targeting is not trivial as there is heterogeneity in firms' attributes and performance, even within narrowly defined industries (Syverson 2014).

Another relevant policy question is related to the existence of potential complementarities between productivity-enhancing investments (e.g., upgrading for exporting, improving managerial capabilities, adopting complementary business solutions). This is because complementarities can make multiple-treatment business support programs more effective than those that provide only one arm of support. For example, recent firm-level evidence on digital-technology adoption shows the importance of making complementary investments and organizational innovations to help adopting firms take advantage of their newly adopted digital business solutions (Brynjolfsson et al. 2020; Brynjolfsson, Rock, and Syverson 2017; Bresnahan, Brynjolfsson, and Hitt 2002).

Panels (a) and (b) of Figure 8.1 show the (log)TFPR-premium from email and website adoption for the typical firm. Based on the estimation sample, the typical firm does not export, does not have a business website, and has a manager with 17 years of experience. Both panels in Figure 8.1 show that for the typical firm, the benefits from digital-technology adoption are decreasing in TFPR. Thus, fostering email or website adoption by laggard firms will deliver higher aggregate productivity gains than promoting adoption by leaders. However, if email or website adoption is coupled with other digital-business solutions and (or) access to foreign markets, then it is better to target high-productivity firms. This is because there are high complementarities between digital-technology business solutions and exporting.

Figure 8.1: $\ln(TFPR)$ **Premium for Typical Firm**

(a) Email **(b) Website**



9 Conclusions

Technological change is altering the way firms produce their goods and services. Yet, estimates about their effects on firm-level productivity and factor demand are scarce, especially for developing economies. Concerns have focused, primarily, around two topics. The first one is the global contraction in productivity growth rates, which occurred despite the spectacular technological progress observed in recent years. The second one is the potential labor-displacement and skill-biased effects of technology adoption by profit-maximizing firms.

This paper presents firm-level estimates of the productivity (TFPR) premium of adopting digital business solutions in manufacturing enterprises in 82 developing countries with data from 2002-2019. It examines the impact of adopting email to connect with clients or suppliers and launching a business website on TFPR and factor demand. The data and methodology appear to be consistent with the existing literature that focuses only on learning by exporting effects. The empirical strategy builds on the Control Function approach and thus controls for the endogeneity of input choices. In addition, we assume an endogenous productivity process that is a function of firm digitization, learning-by-exporting, and managerial experience. At the time of writing, this paper is the only study that utilizes a large sample of enterprises from across the developing world and simultaneously studies the impact of more than one choice variable on both TFPR and factor demand.

The resulting evidence suggests that digital-technology adoption affects manufacturing firm performance in developing countries. However, the productivity-premium from email and website adoption varies across firms, as do the effects of exporting and managerial experience. Nonetheless, estimates of the median effect of digital technology adoption on TFPR indicate that the expected economic magnitudes (probability-adjusted) of these effects are potentially larger for digital-technology adoption than for exporting or enhancing managerial capabilities. Moreover, there is evidence of complementarities among these choice variables when it comes to their impact on TFPR. Finally, on average and contrary to most of the evidence found in the literature, we do not find a digitization-driven displacement effect on jobs or capital. By contrast, digital technology adoption seems to increase firms' demand for labor and capital. Last but not least, the evidence from the rich set of interactions suggests that program targeting in developing economies can yield substantial aggregate TFPR gains relative to random treatment selection.

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Appendix

A Tables

Table 6: Number of observations in WBES by Country and Year

Country	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
Afghanistan	-	-	-	338	-	-	647	-	526	-	-	-	410	-	-	-	-	-	1,921
Albania	170	-	-	204	-	304	-	175	-	-	-	360	-	-	-	-	-	-	1,213
Angola	-	-	-	-	425	-	-	-	360	-	-	-	-	-	-	-	-	-	785
Argentina	-	-	-	-	1,063	-	-	-	1,054	-	-	-	-	-	-	991	-	-	3,108
Armenia	171	-	-	351	-	-	-	374	-	-	-	360	-	-	-	-	-	-	1,256
Azerbaijan	170	-	-	350	-	-	-	380	-	-	-	390	-	-	-	-	-	-	1,290
Bangladesh	-	-	-	-	-	1,504	-	-	-	250	-	1,442	-	-	-	-	-	-	3,196
Belarus	250	-	-	325	-	-	273	-	-	-	-	360	-	-	-	-	600	-	1,808
Benin	-	-	197	-	-	-	-	150	-	-	-	-	-	-	150	-	-	-	497
Bhutan	-	-	-	-	-	-	-	250	-	-	-	-	-	253	-	-	-	-	503
Bolivia	-	-	-	-	613	-	-	-	362	-	-	-	-	-	-	364	-	-	1,339
Bosnia and Herzegovina	182	-	-	200	-	-	-	361	-	-	-	360	-	-	-	-	-	-	1,103
Botswana	-	-	-	-	342	-	-	-	268	-	-	-	-	-	-	-	-	-	610
Brazil	-	1,642	-	-	-	-	-	1,802	-	-	-	-	-	-	-	-	-	-	3,444
Bulgaria	250	-	-	300	-	1,015	-	288	-	-	-	293	-	-	-	-	-	-	2,146
Burkina Faso	-	-	-	-	139	-	-	394	-	-	-	-	-	-	-	-	-	-	533
Cambodia	-	-	-	-	-	-	-	-	-	-	-	472	-	-	373	-	-	-	845
Cameroon	-	-	-	-	207	-	-	363	-	-	-	-	-	-	361	-	-	-	931
Cabo Verde	-	-	-	-	98	-	-	156	-	-	-	-	-	-	-	-	-	-	254
Chad	-	-	-	-	-	-	-	150	-	-	-	-	-	-	-	-	153	-	303
Chile	-	-	-	-	1,017	-	-	-	1,033	-	-	-	-	-	-	-	-	-	2,050
Colombia	-	-	-	-	1,000	-	-	-	942	-	-	-	-	-	-	993	-	-	2,935
Croatia	187	-	-	236	-	633	-	159	-	-	-	360	-	-	-	-	-	-	1,575
Cote d'Ivoire	268	-	-	343	-	-	-	250	-	-	-	254	-	-	-	-	-	-	1,115
Czech Republic	-	-	-	-	-	-	-	526	-	-	-	-	-	-	361	-	-	-	887
Congo, Dem. Rep.	-	-	-	-	340	-	-	-	359	-	-	529	-	-	-	-	-	-	1,228
Dominican Republic	-	-	-	-	-	-	-	-	360	-	-	-	-	-	359	-	-	-	719
Ecuador	-	453	-	-	658	-	-	-	366	-	-	-	-	-	-	361	-	-	1,838
Egypt, Arab Rep.	-	-	977	-	-	1,339	1,700	-	-	-	-	2,897	-	-	1,827	-	-	-	8,740
El Salvador	-	-	-	-	693	-	-	-	360	-	-	-	-	-	719	-	-	-	1,772
Estonia	170	-	-	219	-	-	-	273	-	-	-	273	-	-	-	-	-	-	935
Ethiopia	-	-	-	-	-	-	-	-	-	644	-	-	-	848	-	-	-	-	1,492
Georgia	174	-	-	200	-	-	-	373	-	-	-	360	-	-	-	-	-	-	1,107
Ghana	-	-	-	-	-	494	-	-	-	-	-	720	-	-	-	-	-	-	1,214
Guatemala	-	455	-	-	522	-	-	-	590	-	-	-	-	-	-	345	-	-	1,912
Honduras	-	450	-	-	436	-	-	-	360	-	-	-	-	-	332	-	-	-	1,578
Hungary	250	-	-	610	-	-	-	291	-	-	-	310	-	-	-	-	-	-	1,461
Indonesia	-	-	-	-	-	-	-	1,444	-	-	-	-	-	1,320	-	-	-	-	2,764
Kazakhstan	250	-	-	585	-	-	-	544	-	-	-	600	-	-	-	-	-	-	1,979
Kenya	-	-	-	-	-	657	-	-	-	-	-	781	-	-	-	-	1,001	-	2,439
Kosovo	-	-	-	-	-	-	-	270	-	-	-	202	-	-	-	-	-	-	472
Kyrgyzstan	173	-	-	202	-	-	-	235	-	-	-	270	-	-	-	-	-	360	1,240
Lao PDR	-	-	-	-	-	-	-	360	-	-	379	-	-	-	368	-	332	-	1,439
Latvia	176	-	-	205	-	-	-	271	-	-	-	336	-	-	-	-	-	-	988
Lesotho	-	-	-	-	-	-	-	151	-	-	-	-	-	-	150	-	-	-	301
Total	6,586	4,472	2,024	12,007	13,675	13,104	4,132	22,556	12,398	1,734	4,599	22,180	4,842	4,878	6,875	5,222	2,319	2,023	145,626

Table 6: Number of observations in WBES by Country and Year

Country	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
Liberia	-	-	-	-	-	-	-	150	-	-	-	-	-	-	-	151	-	-	301
Lithuania	200	-	-	205	-	-	-	276	-	-	-	270	-	-	-	-	-	-	951
North Macedonia	170	-	-	200	-	-	-	366	-	-	-	-	-	-	-	-	-	-	736
Malawi	-	-	-	160	-	-	-	150	-	-	-	-	523	-	-	-	-	-	833
Mali	-	155	-	-	-	490	-	-	360	-	-	-	-	-	185	-	-	-	1,190
Mexico	-	-	-	-	1,480	-	-	-	1,480	-	-	-	-	-	-	-	-	-	2,960
Moldova	174	-	-	350	-	-	-	363	-	-	-	360	-	-	-	-	-	-	1,247
Mongolia	-	-	-	-	-	-	-	362	-	-	-	360	-	-	-	-	-	-	722
Montenegro	20	-	-	18	-	-	-	116	-	-	-	150	-	-	-	-	-	-	304
Morocco	-	-	850	-	-	659	-	-	-	-	-	-	-	-	-	-	-	-	1,509
Myanmar	-	-	-	-	-	-	-	-	-	-	-	-	632	-	607	-	-	-	1,239
Nepal	-	-	-	-	-	-	-	486	-	-	-	482	-	-	-	-	-	-	968
Nicaragua	-	452	-	-	478	-	-	-	336	-	-	-	-	-	333	-	-	-	1,599
Niger	-	-	-	138	-	-	-	150	-	-	-	-	-	-	-	151	-	-	439
Nigeria	-	-	-	-	-	2,387	-	3,157	-	-	-	-	2,676	-	-	-	-	-	8,220
Pakistan	402	-	-	-	-	1,337	-	-	-	-	-	906	-	-	-	-	-	-	2,645
Panama	-	-	-	-	604	-	-	-	365	-	-	-	-	-	-	-	-	-	969
Paraguay	-	-	-	-	613	-	-	-	361	-	-	-	-	-	-	364	-	-	1,338
Peru	-	-	-	-	632	-	-	-	1,000	-	-	-	-	-	-	1,003	-	-	2,635
Philippines	-	-	-	-	-	-	-	1,326	-	-	-	-	-	1,335	-	-	-	-	2,661
Poland	500	-	-	975	-	-	-	455	-	-	-	542	-	-	-	-	-	-	2,472
Romania	255	-	-	600	-	-	-	541	-	-	-	540	-	-	-	-	-	-	1,936
Russian Federation	506	-	-	601	-	-	-	1,004	-	-	4,220	-	-	-	-	-	-	-	6,331
Rwanda	-	-	-	-	212	-	-	-	-	241	-	-	-	-	-	-	-	-	453
Senegal	-	262	-	-	-	625	-	-	-	-	-	-	601	-	-	-	-	-	1,488
Serbia	230	-	-	282	-	-	-	388	-	-	-	360	-	-	-	-	-	-	1,260
Sierra Leone	-	-	-	-	-	-	-	150	-	-	-	-	-	-	-	152	-	-	302
Slovak Republic	170	-	-	220	-	-	-	275	-	-	-	268	-	-	-	-	-	-	933
Slovenia	188	-	-	223	-	-	-	276	-	-	-	270	-	-	-	-	-	-	957
South Africa	-	603	-	-	-	1,057	-	-	-	-	-	-	-	-	-	-	-	-	1,660
Suriname	-	-	-	-	-	-	-	-	152	-	-	-	-	-	-	-	233	-	385
Tajikistan	-	-	-	-	-	-	360	-	-	-	-	359	-	-	-	-	-	-	719
Tanzania	-	-	-	-	419	-	-	-	-	-	-	813	-	-	-	-	-	-	1,232
Timor Leste	-	-	-	-	-	-	-	150	-	-	-	-	-	126	-	-	-	-	276
Togo	-	-	-	-	-	-	-	155	-	-	-	-	-	-	150	-	-	-	305
Turkey	-	-	-	1,323	-	-	1,152	-	-	-	-	1,344	-	-	-	-	-	1,663	5,482
Uganda	-	-	-	-	563	-	-	-	-	-	-	762	-	-	-	-	-	-	1,325
Ukraine	463	-	-	594	-	-	-	851	-	-	-	1,002	-	-	-	-	-	-	2,910
Uruguay	-	-	-	-	621	-	-	-	607	-	-	-	-	-	-	347	-	-	1,575
Uzbekistan	260	-	-	300	-	-	-	366	-	-	-	390	-	-	-	-	-	-	1,316
Venezuela, RB	-	-	-	-	500	-	-	-	320	-	-	-	-	-	-	-	-	-	820
Vietnam	-	-	-	1,150	-	-	-	1,053	-	-	-	-	-	996	-	-	-	-	3,199
Yemen, Rep.	-	-	-	-	-	-	-	-	477	-	-	353	-	-	-	-	-	-	830
Zambia	207	-	-	-	-	603	-	-	-	-	-	720	-	-	-	-	-	-	1,530
Zimbabwe	-	-	-	-	-	-	-	-	-	599	-	-	-	-	600	-	-	-	1,199
Total	6,586	4,472	2,024	12,007	13,675	13,104	4,132	22,556	12,398	1,734	4,599	22,180	4,842	4,878	6,875	5,222	2,319	2,023	145,626

Table 7: Number of observations in WBES by Country and Year

Country	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
Afghanistan	-	-	-	18	-	-	115	-	87	-	-	-	132	-	-	-	-	-	352
Albania	65	-	-	76	-	111	-	66	-	-	-	110	-	-	-	-	-	-	428
Angola	-	-	-	-	214	-	-	-	106	-	-	-	-	-	-	-	-	-	320
Argentina	-	-	-	-	695	-	-	-	767	-	-	-	-	-	-	646	-	-	2,108
Armenia	64	-	-	220	-	-	-	106	-	-	-	109	-	-	-	-	-	-	499
Azerbaijan	51	-	-	191	-	-	-	109	-	-	-	120	-	-	-	-	-	-	471
Bangladesh	-	-	-	-	-	926	-	-	-	242	-	1,171	-	-	-	-	-	-	2,339
Belarus	43	-	-	50	-	-	96	-	-	-	-	116	-	-	-	-	330	-	635
Benin	-	-	167	-	-	-	-	74	-	-	-	-	-	-	70	-	-	-	311
Bhutan	-	-	-	-	-	-	-	94	-	-	-	-	-	82	-	-	-	-	176
Bolivia	-	-	-	-	388	-	-	-	154	-	-	-	-	-	-	113	-	-	655
Bosnia and Herzegovina	68	-	-	75	-	-	-	125	-	-	-	117	-	-	-	-	-	-	385
Botswana	-	-	-	-	110	-	-	-	84	-	-	-	-	-	-	-	-	-	194
Brazil	-	1,606	-	-	-	-	-	1,481	-	-	-	-	-	-	-	-	-	-	3,087
Bulgaria	50	-	-	57	-	634	-	87	-	-	-	109	-	-	-	-	-	-	937
Burkina Faso	-	-	-	-	52	-	-	94	-	-	-	-	-	-	-	-	-	-	146
Cambodia	-	-	-	-	-	-	-	-	-	-	-	46	-	-	134	-	-	-	180
Cameroon	-	-	-	-	106	-	-	103	-	-	-	-	-	-	97	-	-	-	306
Cabo Verde	-	-	-	-	44	-	-	63	-	-	-	-	-	-	-	-	-	-	107
Chad	-	-	-	-	-	-	-	59	-	-	-	-	-	-	-	-	74	-	133
Chile	-	-	-	-	656	-	-	-	779	-	-	-	-	-	-	-	-	-	1,435
Colombia	-	-	-	-	647	-	-	-	700	-	-	-	-	-	-	563	-	-	1,910
Croatia	40	-	-	74	-	408	-	59	-	-	-	121	-	-	-	-	-	-	702
Côte d'Ivoire	70	-	-	82	-	-	-	97	-	-	-	112	-	-	-	-	-	-	361
Czech Republic	-	-	-	-	-	-	-	195	-	-	-	-	-	-	102	-	-	-	297
Congo, Dem. Rep.	-	-	-	-	144	-	-	-	125	-	-	236	-	-	-	-	-	-	505
Dominican Republic	-	-	-	-	-	-	-	-	115	-	-	-	-	-	108	-	-	-	223
Ecuador	-	156	-	-	360	-	-	-	126	-	-	-	-	-	-	103	-	-	745
Egypt, Arab Rep.	-	-	578	-	-	767	1,112	-	-	-	-	1,935	-	-	1,156	-	-	-	5,548
El Salvador	-	-	-	-	445	-	-	-	131	-	-	-	-	-	405	-	-	-	981
Estonia	29	-	-	39	-	-	-	86	-	-	-	82	-	-	-	-	-	-	236
Ethiopia	-	-	-	-	-	-	-	-	-	299	-	-	-	380	-	-	-	-	679
Georgia	32	-	-	48	-	-	-	117	-	-	-	110	-	-	-	-	-	-	307
Ghana	-	-	-	-	-	290	-	-	-	-	-	374	-	-	-	-	-	-	664
Guatemala	-	410	-	-	315	-	-	-	349	-	-	-	-	-	-	141	-	-	1,215
Honduras	-	450	-	-	285	-	-	-	183	-	-	-	-	-	90	-	-	-	1,008
Hungary	51	-	-	355	-	-	-	110	-	-	-	97	-	-	-	-	-	-	613
Indonesia	-	-	-	-	-	-	-	1,131	-	-	-	-	-	1,067	-	-	-	-	2,198
Kazakhstan	55	-	-	345	-	-	-	186	-	-	-	200	-	-	-	-	-	-	786
Kenya	-	-	-	-	-	388	-	-	-	-	-	383	-	-	-	-	425	-	1,196
Kosovo	-	-	-	-	-	-	-	90	-	-	-	71	-	-	-	-	-	-	161
Kyrgyzstan	49	-	-	58	-	-	-	93	-	-	-	105	-	-	-	-	-	145	450
Lao PDR	-	-	-	-	-	-	-	143	-	-	86	-	-	-	115	-	134	-	478
Latvia	28	-	-	35	-	-	-	90	-	-	-	114	-	-	-	-	-	-	267
Lesotho	-	-	-	-	-	-	-	31	-	-	-	-	-	-	74	-	-	-	105
Total	1,602	3,766	1,566	5,886	7,880	6,727	2,319	11,106	6,909	973	1,443	11,046	2,169	3,306	3,246	2,533	1,042	1,204	74,723

Table 7: Number of observations in WBES by Country and Year

Country	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
Liberia	-	-	-	-	-	-	-	48	-	-	-	-	-	-	-	75	-	-	123
Lithuania	42	-	-	45	-	-	-	101	-	-	-	107	-	-	-	-	-	-	295
North Macedonia	47	-	-	58	-	-	-	100	-	-	-	-	-	-	-	-	-	-	205
Malawi	-	-	-	59	-	-	-	70	-	-	-	-	196	-	-	-	-	-	325
Mali	-	63	-	-	-	301	-	-	165	-	-	-	-	-	98	-	-	-	627
Mexico	-	-	-	-	1,059	-	-	-	1,154	-	-	-	-	-	-	-	-	-	2,213
Moldova	49	-	-	193	-	-	-	105	-	-	-	110	-	-	-	-	-	-	457
Mongolia	-	-	-	-	-	-	-	127	-	-	-	115	-	-	-	-	-	-	242
Montenegro	7	-	-	4	-	-	-	38	-	-	-	49	-	-	-	-	-	-	98
Morocco	-	-	821	-	-	451	-	-	-	-	-	-	-	-	-	-	-	-	1,272
Myanmar	-	-	-	-	-	-	-	-	-	-	-	-	334	-	360	-	-	-	694
Nepal	-	-	-	-	-	-	-	165	-	-	-	239	-	-	-	-	-	-	404
Nicaragua	-	430	-	-	343	-	-	-	127	-	-	-	-	-	104	-	-	-	1,004
Niger	-	-	-	37	-	-	-	46	-	-	-	-	-	-	-	41	-	-	124
Nigeria	-	-	-	-	-	1,035	-	1,594	-	-	-	-	1,261	-	-	-	-	-	3,890
Pakistan	36	-	-	-	-	102	-	-	-	-	-	661	-	-	-	-	-	-	799
Panama	-	-	-	-	239	-	-	-	115	-	-	-	-	-	-	-	-	-	354
Paraguay	-	-	-	-	387	-	-	-	143	-	-	-	-	-	-	117	-	-	647
Peru	-	-	-	-	362	-	-	-	751	-	-	-	-	-	-	547	-	-	1,660
Philippines	-	-	-	-	-	-	-	937	-	-	-	-	-	1,027	-	-	-	-	1,964
Poland	120	-	-	520	-	-	-	140	-	-	-	183	-	-	-	-	-	-	963
Romania	83	-	-	381	-	-	-	178	-	-	-	169	-	-	-	-	-	-	811
Russian Federation	125	-	-	143	-	-	-	687	-	-	1,357	-	-	-	-	-	-	-	2,312
Rwanda	-	-	-	-	30	-	-	-	-	78	-	-	-	-	-	-	-	-	108
Senegal	-	63	-	-	-	273	-	-	-	-	-	-	246	-	-	-	-	-	582
Serbia	61	-	-	84	-	-	-	139	-	-	-	117	-	-	-	-	-	-	401
Sierra Leone	-	-	-	-	-	-	-	35	-	-	-	-	-	-	-	77	-	-	112
Slovak Republic	32	-	-	39	-	-	-	85	-	-	-	100	-	-	-	-	-	-	256
Slovenia	45	-	-	58	-	-	-	101	-	-	-	84	-	-	-	-	-	-	288
South Africa	-	588	-	-	-	708	-	-	-	-	-	-	-	-	-	-	-	-	1,296
Suriname	-	-	-	-	-	-	-	-	76	-	-	-	-	-	-	-	79	-	155
Tajikistan	-	-	-	-	-	-	111	-	-	-	-	121	-	-	-	-	-	-	232
Tanzania	-	-	-	-	273	-	-	-	-	-	-	427	-	-	-	-	-	-	700
Timor Leste	-	-	-	-	-	-	-	56	-	-	-	-	-	60	-	-	-	-	116
Togo	-	-	-	-	-	-	-	36	-	-	-	-	-	-	45	-	-	-	81
Turkey	-	-	-	1,235	-	-	885	-	-	-	-	1,050	-	-	-	-	-	1,059	4,229
Uganda	-	-	-	-	304	-	-	-	-	-	-	358	-	-	-	-	-	-	662
Ukraine	140	-	-	182	-	-	-	557	-	-	-	717	-	-	-	-	-	-	1,596
Uruguay	-	-	-	-	375	-	-	-	371	-	-	-	-	-	-	110	-	-	856
Uzbekistan	52	-	-	72	-	-	-	124	-	-	-	132	-	-	-	-	-	-	380
Venezuela, RB	-	-	-	-	47	-	-	-	81	-	-	-	-	-	-	-	-	-	128
Vietnam	-	-	-	1,053	-	-	-	748	-	-	-	-	-	690	-	-	-	-	2,491
Yemen, Rep.	-	-	-	-	-	-	-	-	220	-	-	108	-	-	-	-	-	-	328
Zambia	68	-	-	-	-	333	-	-	-	-	-	361	-	-	-	-	-	-	762
Zimbabwe	-	-	-	-	-	-	-	-	-	354	-	-	-	-	288	-	-	-	642
Total	1,602	3,766	1,566	5,886	7,880	6,727	2,319	11,106	6,909	973	1,443	11,046	2,169	3,306	3,246	2,533	1,042	1,204	74,723

Table 8: Descriptive Statistics of observations in Manufacturing Industries

Sector Description	Imputation					No Imputation				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Sales	64,149	16.8	3.4	0.6	33.8	64,137	16.8	3.4	0.6	33.8
Capital	63,162	14.8	3.7	0.5	36.5	50,199	14.9	3.8	0.5	36.5
Materials	62,699	15.4	3.7	0.5	32.1	50,959	15.6	3.7	0.5	32.1
Labor	73,124	3.6	1.4	0.1	11.1	73,011	3.6	1.4	0.7	11.1
Investment	60,581	13.4	3.5	0.5	35.6	31,248	13.7	3.7	0.5	35.6
Export Status	63,569	0.3	0.4	0.0	1.0	63,569	0.3	0.4	0.0	1.0
Managerial Experience	65,664	17.8	11.8	0.0	75.0	65,664	17.8	11.8	0.0	75.0
E-mail Adoption	68,390	0.7	0.5	0.0	1.0	68,390	0.7	0.5	0.0	1.0
Website Adoption	71,769	0.4	0.5	0.0	1.0	71,769	0.4	0.5	0.0	1.0

Note: The descriptive statistics for sales, capital, materials, labor and investment are in natural logarithms. The following questions from the World Bank Enterprise Survey questionnaire have been used to create the variables for our empirical analysis: Sales: In fiscal year [insert last complete fiscal year], what were this establishment's total annual sales for ALL products and services?; Capital: From this establishment's Balance Sheet for fiscal year [insert last complete fiscal year], what was the net book value, that is the value of assets after depreciation, of the Machinery, vehicles, and equipment?; Materials: From this establishment's Income Statement for fiscal year [insert last complete fiscal year], please provide the total annual cost of raw materials and intermediate goods used in production?; Labor: At the end of fiscal year [insert last complete fiscal year], how many permanent, full-time individuals worked in this establishment?; Investment: In fiscal year [insert last complete fiscal year], how much did this establishment spend on purchases of new or used machinery, vehicles, and equipment?; Export Status: Coming back to fiscal year [insert last complete fiscal year], what percentage of this establishment's sales were direct exports?; Managerial Experience: How many years of experience working in this sector does the Top Manager have?; Email: At the present time, does this establishment use e-mail to communicate with clients or suppliers?; Website: At the present time, does this establishment have its own website?

Table 9: Descriptive Statistics of observations in Manufacturing Industries

Variables	Imputation				
	Obs	Mean	Std. Dev.	Min	Max
Sales	64,149	16.8	3.4	0.6	33.8
Capital	63,162	14.8	3.7	0.5	36.5
Materials	62,699	15.4	3.7	0.5	32.1
Labor	73,124	3.6	1.4	0.1	11.1
Investment	60,581	13.4	3.5	0.5	35.6
Export Status	63,569	0.3	0.4	0.0	1.0
Managerial Experience	65,664	17.8	11.8	0.0	75.0
E-mail Adoption	68,390	0.7	0.5	0.0	1.0
Website Adoption	71,769	0.4	0.5	0.0	1.0

Note: The descriptive statistics for sales, capital, materials, labor and investment are in natural logarithms. The following questions from the World Bank Enterprise Survey questionnaire have been used to create the variables for our empirical analysis: Sales: In fiscal year [insert last complete fiscal year], what were this establishment's total annual sales for ALL products and services?; Capital: From this establishment's Balance Sheet for fiscal year [insert last complete fiscal year], what was the net book value, that is the value of assets after depreciation, of the Machinery, vehicles, and equipment?; Materials: From this establishment's Income Statement for fiscal year [insert last complete fiscal year], please provide the total annual cost of raw materials and intermediate goods used in production?; Labor: At the end of fiscal year [insert last complete fiscal year], how many permanent, full-time individuals worked in this establishment?; Investment: In fiscal year [insert last complete fiscal year], how much did this establishment spend on purchases of new or used machinery, vehicles, and equipment?; Export Status: Coming back to fiscal year [insert last complete fiscal year], what percentage of this establishment's sales were direct exports?; Managerial Experience: How many years of experience working in this sector does the Top Manager have?; Email: At the present time, does this establishment use e-mail to communicate with clients or suppliers?; Website: At the present time, does this establishment have its own website?

B Proof: Estimates of Homogeneous Coefficients Reflect Sectoral-Weighted Averages of Estimates of Heterogeneous Coefficients

Suppose we have the following GMM estimator:

$$\hat{\theta} = \underbrace{\left[\left(\sum_{i=1}^{N} X_i' Z_i\right) A \left(\sum_{i=1}^{N} Z_i' X_i\right)\right]^{-1}}_{\Psi} \underbrace{\left[\left(\sum_{i=1}^{N} X_i' Z_i\right) A \left(\sum_{i=1}^{N} X_i' y_i\right)\right]}_{\Phi}, \tag{B.1}$$

where X is a $K \times N$ matrix of regressors, Z is a $Q \times N$ matrix of instruments, A is a $K \times K$ weighting matrix, and y is a $1 \times N$ vector.

The first bracket is a matrix of dimension $K \times K$, which is constructed based on a sample of size N:

$$\left[\left(\sum_{i=1}^{N} X_i' Z_i\right) A \left(\sum_{i=1}^{N} Z_i' X_i\right)\right]^{-1} = \kappa_1 \underbrace{\left[\left(\sum_{i=1}^{N_1} X_i' Z_i\right) A_1 \left(\sum_{i=1}^{N_1} Z_i' X_i\right)\right]^{-1}}_{\Psi_1} \tag{B.2}$$

$$\left[\left(\sum_{i=1}^{N} X_i' Z_i\right) A \left(\sum_{i=1}^{N} Z_i' X_i\right)\right]^{-1} = \kappa_2 \underbrace{\left[\left(\sum_{N_1+1=1}^{N} X_i' Z_i\right) A_2 \left(\sum_{N_1+1=1}^{N} Z_i' X_i\right)\right]^{-1}}_{\Psi_2} \tag{B.3}$$

N-size sample can be divided into two samples of size $N_1$and N_2, where $N = N_1 + N_2$. κ_1 and κ_2 are matrices mapping each component in Ψ to each component in $\Psi_1$and in Ψ_2.

The second component, Φ, is additive. Therefore, it can be written as the sum of the two components corresponding to the two sub-samples:

$$\left[\left(\sum_{i=1}^{N} X_i' Z_i\right) A \left(\sum_{i=1}^{N} X_i' y_i\right)\right] = \underbrace{\left[\left(\sum_{i=1}^{N_1} X_i' Z_i\right) A_1 \left(\sum_{i=1}^{N_1} X_i' y_i\right)\right]}_{\Phi_1} + \underbrace{\left[\left(\sum_{N_1+1=1}^{N} X_i' Z_i\right) A_2 \left(\sum_{N_1+1=1}^{N} X_i' y_i\right)\right]}_{\Phi_2}. \tag{B.4}$$

Replacing B.2 - B.4 into B.1, we can write $\hat{\theta}$ in the following way:

$$\hat{\theta} = \kappa_1 \Psi_1 \Phi_1 + \kappa_2 \Psi_2 \Phi_2.$$

That is, the GMM estimator corresponding to the full sample can be written as a weighted sum of the two estimators corresponding to subsamples 1 and 2.